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ARTIFICIAL INTELLIGENCE FOR OBJECT DETECTION AND ITS METADATA

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ABSTRACT

In the ever-evolving field of computer vision, the infusion of artificial intelligence (AI) has inaugurated a revolutionary era, providing unparalleled precision and efficiency in identifying objects within images and videos. This exploration delves into the domain of AI-driven object detection, emphasizing metadata's pivotal role in enhancing the understanding and utility of recognized entities. The collaboration between AI and metadata enhances the precision of object detection and opens up novel avenues for extracting and analyzing information.

The significance of metadata is underscored as it contributes context and categorization to identified objects. This metadata encompasses crucial details such as object class, detection location, time of occurrence, and inter-object relationships, furnishing invaluable insights for downstream applications like autonomous vehicles, surveillance, and augmented reality. The research paper showcases the seamless integration of metadata extraction and management with AI-powered object detection systems, thereby boosting the accuracy of object identification and tracking.

This study sheds light on the intricate interplay between artificial intelligence and computer vision, molding a landscape where precision and adaptability redefine the boundaries of object detection capabilities.

Keywords: Artificial Intelligence (AI), Machine Learning (ML), Internet of Things (IOT) Data Science, Data Analysis, Data Processing, Data Presentations, and Data Science careers

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INTRODUCTION

Artificial Intelligence (AI) has significantly advanced in computer vision, particularly object detection. This paper explores how AI has transformed object detection, emphasizing the crucial role of metadata in enhancing its capabilities.

In the digital era, the abundance of visual data, from surveillance to medical imaging and self-driving cars, necessitates accurate object detection. AI, especially with deep learning models like convolutional neural networks (CNNs), has become a robust solution, overcoming challenges such as occlusion and scale variations with increasing accuracy.

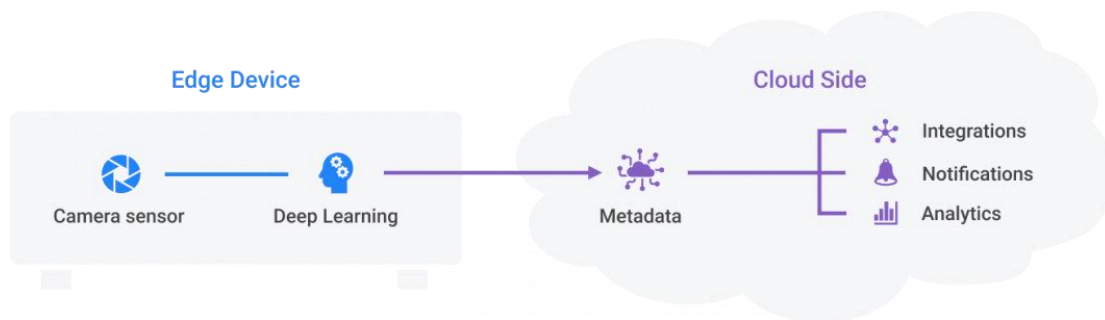
AI, especially utilizing CNNs, has revolutionized object detection in various sectors dealing with vast visual data. These models excel in acquiring hierarchical feature representations, adapting to the dynamic nature of visual input, and continuously improving comprehension.

Object detection faces challenges like occlusion and background clutter. Through continuous learning and sophisticated algorithms, AI techniques adeptly address these challenges. The adaptive nature of AI allows the development of nuanced models for accurate detection in complex environments.

While AI enhances object detection, metadata is crucial, providing additional information such as object class, position, detection time, and associations. Integrating metadata with AI-driven systems transforms the comprehension and utility of identified objects.

Metadata goes beyond visual identification, adding context to detected objects. Understanding object class, location, and temporal occurrence enhances visual data interpretation, contributing to richer information. In downstream applications like augmented reality and surveillance, metadata becomes invaluable, aiding in informed decision-making.

The study demonstrates the seamless integration of AI object identification systems with metadata extraction. This integration enhances object tracking and recognition accuracy, paving the way for sophisticated decision-making across various applications.



Consequences of AI-Powered Object Identification and Integration with Metadata

Integrating AI with metadata for object detection has far-reaching consequences, extending beyond a single domain. This synergy can revolutionize various industries, enhancing security measures and industrial automation capabilities.

The central focus of this paper is the crucial integration of metadata with AI object detection systems, representing a defining aspect of the exploration. Metadata, containing contextual information about detected objects, becomes pivotal for unlocking the full potential of object detection. It includes critical details like object class, detection location, time, and inter-object relationships. This symbiosis between AI and metadata refines object identification and tracking and finds applications in sectors like autonomous vehicles, surveillance, and augmented reality.

The implications of the collaboration between AI and metadata extend into heightened security protocols, increased efficiency in industrial automation, and a deeper understanding of the visual environment. Ethical and privacy concerns related to AI-driven object detection and metadata are also addressed in this paper. This introduction sets the stage for a comprehensive exploration of AI in object detection and its synergistic interplay with metadata, offering insights into the transformative potential of these technologies. It provides a glimpse into a future where intelligent object detection systems redefine our perception and interaction with the visual world.

Object detection in computer vision involves locating and identifying items in images or video frames, going beyond mere identification to accurately define their locations using bounding boxes. This technical advancement is fundamental to applications like robots, augmented reality, driverless cars, and surveillance systems, shaping how machines perceive and interact with their visual surroundings.

Object detection commonly involves the following fundamental elements:

Identifying the position and dimensions of objects within an image. This is often visualized by outlining objects with bounding boxes, specifying their spatial coordinates (x, y) and dimensions (width and height).

Assigning a label or category to each detected object, indicating its type. For instance, in a scene with diverse objects, object detection can discern whether there are cars, pedestrians, animals, or other entities and assign corresponding labels.

Deep learning models, such as convolutional neural networks (CNNs), are frequently employed for object detection. These models are designed to handle both localization and classification tasks concurrently. Through training on extensive datasets with labeled images, they can recognize objects and accurately determine their positions.

Effectively training object detection models necessitates large datasets with annotated images. These datasets typically include images where objects of interest are labeled with bounding boxes and associated class labels. During training, models learn from these examples to precisely predict object positions and classes in new, unseen images.

What makes object detection crucial?

Object detection holds significant importance in computer vision for various reasons. The key rationales for its significance include:

1. Visual Scene Content Interpretation:

Object detection aids in interpreting the content of visual scenes. It enables computers to identify and locate objects, providing context for more sophisticated processing. Object detection is crucial in industrial settings for monitoring product movement, automating processes, and ensuring quality control. Additionally, it promotes greater independence for individuals with visual impairments by recognizing and characterizing objects and their locations.

2. Obstacle Avoidance and Navigation:

Object detection is essential for identifying and avoiding obstacles, navigating surroundings, and making decisions based on the presence of objects. This is particularly crucial in autonomous vehicles, drones, and robotics applications. For security and surveillance systems, object detection enables real-time identification and monitoring of items and people, enhancing threat detection and response. In retail, it automates checkout procedures, tracks products on shelves, and manages inventory for improved productivity and consumer satisfaction.

3. Medical Imaging and Diagnosis:

In medical imaging, object detection aids in locating and identifying specific structures, contributing to diagnosis and therapy. It ensures precision in identifying objects within images, facilitating better healthcare outcomes.

4. Interactive Experiences and Entertainment:

Object detection follows user movements and gestures in interactive applications and games, creating immersive experiences. It automatically tags and categorizes films and images, simplifying the search and organization of extensive media collections.

5. Automation and Speeding Up Processes:

Object detection automates tasks across various industries, reducing the need for manual involvement and accelerating procedures. Augmented reality (AR) applications recognize real-world objects through object detection, enhancing user experiences by overlaying digital data or graphics. Combining object detection with natural language processing (NLP) bridges information gaps between text and images, facilitating content comprehension.

6. Environmental Monitoring and Wildlife Research:

Researchers and conservationists benefit from object detection by obtaining crucial data for tracking environmental changes, monitoring wildlife, and studying animal behavior. It plays a pivotal role in understanding and preserving ecosystems.

Object detection is a versatile and indispensable technology with applications ranging from industrial automation to healthcare, security, entertainment, and environmental conservation.

Object Detection and the Impact of Deep Learning

The realms of object detection and deep learning are intricately linked, with deep learning techniques profoundly shaping the landscape of object detection. The advent of deep learning has brought about a paradigm shift, enhancing the accuracy and efficiency of object detection systems to handle intricate tasks with remarkable precision. Let's delve into the intricate connection between object detection and deep learning:

CNNs, in particular, are deep learning models that include specialized convolutional layers that are skilled at extracting spatial information from images. These layers are excellent at recognizing objects because they can recognize linkages and local patterns among pixels. Models pre-trained on large datasets (like ImageNet) can be refined for particular item recognition tasks using relatively small, labeled datasets thanks to deep learning's support for transfer learning. As a result, less training data is needed for functions involving bespoke object detection.

Convolutional neural networks (CNNs) are deep learning models that show proficiency in automatically extracting hierarchical features from images. Acquired traits are essential for differentiating objects with different sizes, shapes, and orientations. Deep neural networks can capture high-level features that represent the components and structures of an item and low-level features like edges and textures. Learning The benefit of end-to-end training for object localization and classification is provided by deep learning models. This suggests that an individual model can recognize things and anticipate where they will be found in an image instead of conventional computer vision techniques that call for distinct, labor-intensive phases for object recognition and feature extraction.

A wide range of object sizes, types, and degrees of complexity may be handled by deep learning models with versatility. They may adapt to real-world events and are not limited to simple items or shapes.

Deep learning models are particularly good at handling partially veiled or occluded objects. Their capacity to pick up on intricate object appearances makes it easier to identify objects even when they are partially obscured. Ongoing research and advancements in deep learning contribute to the continual enhancement of the accuracy and speed of object detection systems. This ongoing progress renders them suitable for an expanding range of applications.

Large, labeled datasets are essential for the effectiveness of deep learning-based item detection. Deep learning models may learn from various examples, increasing their accuracy and robustness. This is made possible by the availability of large image datasets that have been tagged with object locations and class labels. Researchers have introduced deep learning architectures specifically designed for object detection. Examples include SSD (Single Shot MultiBox Detector), YOLO (You Only Look Once), and Faster R-CNN. These designs effectively combine localization and classification to optimize tasks related to object identification.

Deep learning has made real-time object detection possible, allowing for high-speed object tracking and recognition in applications like augmented reality, video surveillance, and autonomous cars.

ChatGPT

The realms of object detection and deep learning are intricately connected, with deep learning techniques significantly influencing and enhancing the landscape of object detection. The introduction of deep learning has led to a paradigm shift, considerably improving the precision and efficiency of object detection systems for handling complex tasks.

1. Role of Convolutional Neural Networks (CNNs):

CNNs, a deep learning model, feature specialized convolutional layers adept at extracting spatial information from images. These layers excel at recognizing objects by identifying linkages and local patterns among pixels. Pretrained models, such as those on ImageNet, can be fine-tuned for specific object recognition tasks using smaller labeled datasets, showcasing the transfer learning capabilities of deep learning and reducing the need for extensive training data.

2. Hierarchical Feature Extraction:

CNNs automatically extract hierarchical features from images, which is crucial for distinguishing objects with varying sizes, shapes, and orientations. These models capture high-level features representing components and low-level features like edges and textures. End-to-end training facilitates object localization and classification within a single model, eliminating the need for separate, labor-intensive phases in conventional computer vision techniques.

3. Versatility and Adaptability:

Deep learning models exhibit versatility in handling various object sizes, types, and complexities. They can adapt to real-world scenarios and are not limited to simple objects or shapes. Notably, deep learning models excel at handling partially veiled or occluded objects, thanks to their ability to recognize intricate object appearances even when partially obscured. Ongoing research contributes to continuous improvements in the accuracy and speed of object detection systems, expanding their applicability.

4. Importance of Large, Labeled Datasets:

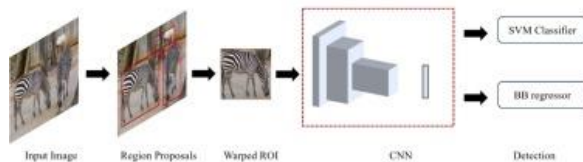
Large, labeled datasets are essential for the effectiveness of deep learning-based object detection. These datasets enable models to learn from diverse examples, enhancing their accuracy and robustness. Researchers have introduced specialized deep learning architectures for object detection, such as SSD, YOLO, and Faster R-CNN, which efficiently combine localization and classification to optimize object identification tasks.

5. Real-Time Object Detection:

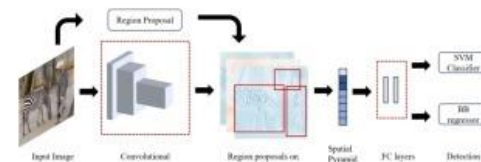
Deep learning has enabled real-time object detection, facilitating high-speed object tracking and recognition in applications like augmented reality, video surveillance, and autonomous vehicles.

The marriage of object detection and deep learning, mainly through CNNs and other specialized architectures, has ushered in a transformative era, offering enhanced accuracy, adaptability, and real-time capabilities across diverse applications. Ongoing advancements in deep learning continue to push the boundaries of what is achievable in object detection.

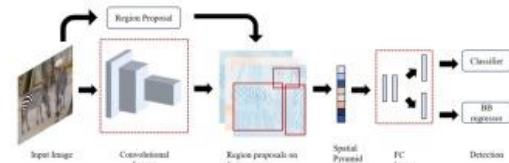
RCNN



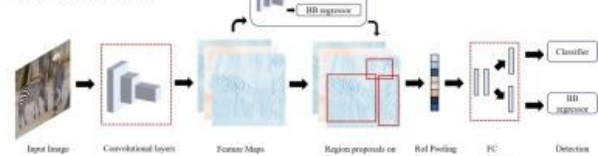
SPP-Net



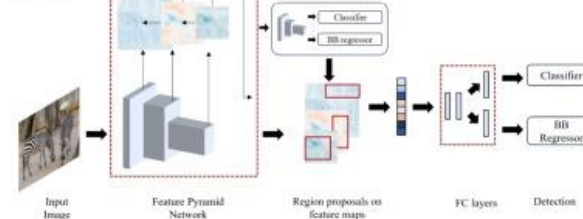
Fast RCNN



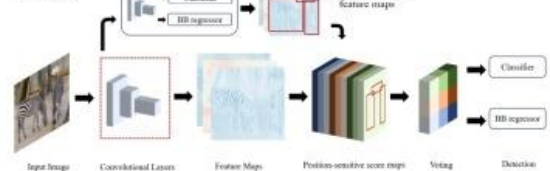
Faster RCNN



FPN



R-FCN



How Object Detection Operates

Object detection, a critical computer vision task, involves using algorithms, particularly deep learning models, to identify and locate objects within images or video frames. The operational process of object detection can be broken down as follows:

1. Data Gathering and Preparation:

Collect a dataset comprising images or video frames displaying objects of interest.

Label each image with bounding boxes indicating the object's location and class labels specifying the object type (e.g., "car," "person," "cat").

2. Selection of Deep Learning Model:

For object detection, utilize deep learning models, especially convolutional neural networks (CNNs).

Various models like SSD, RetinaNet, YOLO, and Faster R-CNN address specific application, speed, and accuracy concerns.

3. Training the Model:

Train the selected deep learning model using the prepared dataset.

Adjust internal parameters to minimize the difference between model predictions and ground truth (labeled bounding boxes and class labels).

Optimize a loss function measuring the discrepancy between predicted and actual object positions and classifications through an iterative training process.

4. Inference:

After training, use the model to identify objects in new, unlabeled images or video frames.

During inference, analyze the image either as a whole or by segmenting it into smaller regions based on the model architecture.

5. Prediction Outputs:

Generate predictions for each region, including:

Bounding boxes (coordinates) around local objects.

Class designations corresponding to the identified objects.

Confidence scores indicate the model's confidence in each prediction.

6. Post-Processing:

Address repetitive boxes or predictions with low confidence scores using post-processing techniques.

Non-maximum suppression (NMS) is one such method to eliminate redundant boxes, retaining the most accurate and confident predictions.

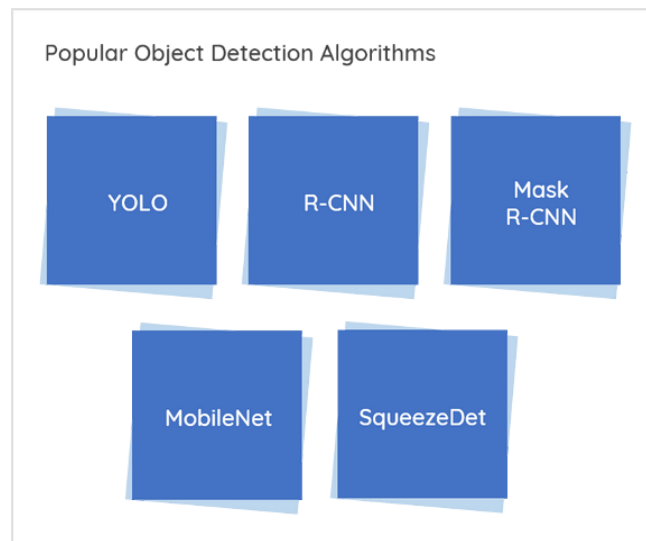
7. Final Results:

Draw bounding boxes around objects in the image to represent the final object detection results, including position and class information.

8. Applications:

Apply object detection findings in various domains, such as augmented reality, safety systems, autonomous vehicle decision-making, and object tracking.

Most Popular Object Detection Algorithms



Convolutional neural networks, such as Mask R-CNN, R-CNN (Region-Based Convolutional Neural Networks), YOLO (You Only Look Once), MobileNet, and SqueezeDet, are frequently used methods for object detection.

R-CNN:

The Region-based Convolutional Neural Network (R-CNN) is a computer vision model designed for object recognition and image detection. Here's a breakdown of its functionality:

1. Region Proposal:

R-CNN begins by identifying potential objects in an image using a "selective search method," suggesting areas likely to contain objects.

2. Convolutional Neural Network (CNN) Analysis:

R-CNN utilizes a CNN for each suggested region to analyze and understand the content, creating a descriptive map of the area.

3. Support Vector Machine (SVM):

R-CNN applies a support vector machine to identify the objects present in the regions. It categorizes and recognizes objects using labels.

4. Bounding Box Refinement:

The model refines the bounding boxes surrounding the recognized objects, adjusting them to match the shapes of the objects better.

5. Result Selection:

R-CNN selects the most accurate and confident outcomes, eliminating less trustworthy ones to prevent displaying excessively similar findings.

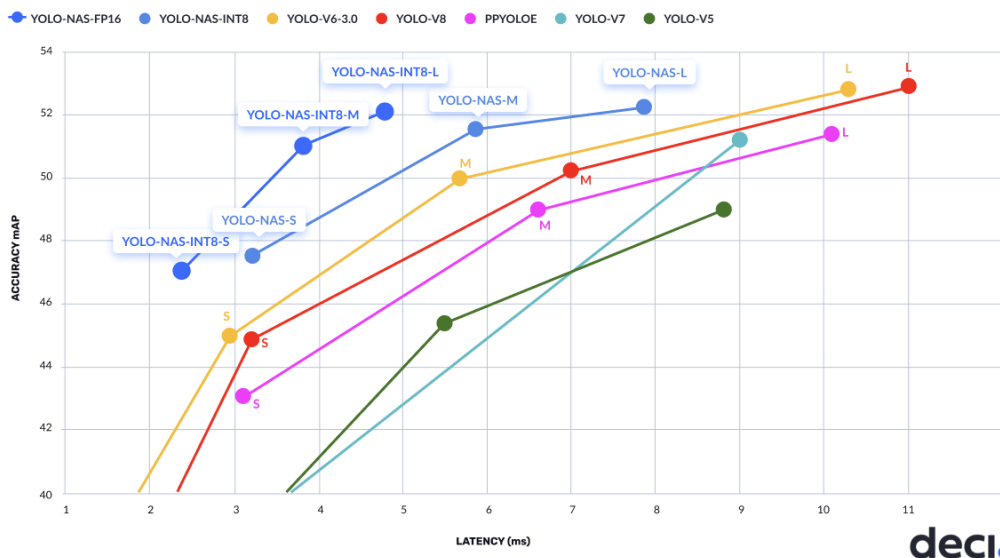
6. Drawbacks and Enhancements:

R-CNN, while a breakthrough, was slow and complex for object identification. Later models like Fast R-CNN and Faster R-CNN addressed these issues, introducing improvements for increased accuracy and speed in object detection.

Mask R-CNN:

- An extension of Faster R-CNN, Mask R-CNN, introduced in 2017, handles instance segmentation, providing pixel-level masks for each unique instance of an object in addition to object detection.
- Mask R-CNN utilizes a CNN to extract features, refines bounding boxes for precise object fitting, and creates binary masks to identify pixel-level object instances.
- The model groups identified items into various types or categories and employed non-maximum suppression to remove duplicate or overlapping results after object detection, mask creation, and classification.
- Applications for Mask R-CNN are found in domains requiring instance-level segmentation and pixel-level precision, such as robotics, computer vision tasks, and medical imaging.

Efficient Frontier of Object Detection on COCO, Measured on NVIDIA T4



Deep learning-based object identification models are crucial in recognizing items in images or video frames and delineating them with bounding boxes. After object detection, metadata models come into play, focusing on obtaining additional data or characteristics associated with the detected objects. The extracted metadata is linked to each bounding box, providing precise attribute descriptions for each recognized object. Here are some common metadata attributes:

- Object Class: Identifying the type of object (e.g., "car," "person," "dog").
- Color: Specifying the object's color or color patterns.
- Size: Determining the object's actual dimensions.
- Orientation: Identifying the object's orientation or position.
- Velocity: Determining the motion or speed of the object.
- Timestamp: Documenting the moment the object was detected.
- Context: Recognizing how an object fits into its surroundings or connects to other objects.

Combining spatial information from the bounding box with associated metadata enables pinpointing specific characteristics of individual objects. For instance, metadata might describe a detected car as "red," "sedan," and "parked."

Applications for combined object detection and metadata information span various fields:

- **Traffic Monitoring:** Identifying vehicle types, colors, and speeds for traffic studies.
- **Security and Surveillance:** Sorting individuals and items based on potential threats.
- **Autonomous Vehicles:** Recognizing characteristics and motion of nearby automobiles and people.
- **Retail Inventory:** Monitoring goods on store shelves, including locations and attributes.
- **Augmented Reality:** Overlaying digital data based on identified items and their characteristics.
- **Medical Imaging:** Analyzing and recording characteristics of anatomical structures or anomalies.

Combining object detection and metadata models provides a comprehensive and contextual understanding of objects within an image or video frame. This information enhances the utility and functionality of computer vision systems, enabling improved decision-making, analysis, and automation across diverse fields.

YOLO (You Only Look Once):

YOLO (You Only Look Once) is a real-time object detection system widely popular in computer vision and deep learning. Introduced by Joseph Redmon and Santosh Divvala in a series of papers, the original paper titled "You Only Look Once: Unified, Real-Time Object Detection" was published in 2016. YOLO is designed for instantaneous object detection in video and image streams, quickly locating and identifying multiple objects in a single neural network pass.

Key features and aspects of YOLO include:

1. Unified Approach:

- YOLO takes a unique approach by splitting the image into a grid and predicting bounding boxes and class probabilities for every grid cell. Unlike region-based object identification techniques like R-CNN, YOLO analyzes the entire image in a single pass.

2. Single Pass Analysis:

- YOLO effectively analyzes the complete picture in one pass, providing predictions for every object simultaneously. This architecture significantly improves speed compared to traditional techniques that require multiple network passes.

3. Bounding Box Prediction:

- YOLO predicts bounding boxes that define the locations of objects for each grid cell. Confidence scores indicate the accuracy of predictions. Class probability predictions are also used to identify the object type in each bounding box.

4. Non-Maximum Suppression:

- YOLO uses non-maximum suppression to eliminate redundant bounding boxes, retaining the most reliable and accurate ones. This post-prediction step is performed for every grid cell.

5. Iterative Improvements:

- YOLO has undergone several revisions, including YOLOv1, YOLOv2 (YOLO9000), YOLOv3, and YOLOv4. Each iteration has surpassed the previous ones in accuracy and speed, solidifying YOLO's reputation as a flexible option for various object detection applications.

6. Applications:

- YOLO's strength lies in its high-precision real-time object identification capability, making it ideal for applications such as robots, autonomous cars, surveillance, and more.

7. Ongoing Relevance:

- YOLO is still frequently used in computer vision and has inspired the development of other real-time object detection methods.
- YOLO's innovative approach to real-time object detection, combined with its iterative improvements, has made it a widely adopted and versatile solution for various applications in the field of computer vision.

MobileNet

MobileNet is a family of simplified convolutional neural network architectures designed for efficient and low-latency deep learning inference on mobile and embedded devices. Developed by Google's Research Brain Team, MobileNet prioritizes high performance within a small memory and computational framework. Notable features include using depthwise separable convolutions and dividing the convolution process into depthwise and pointwise stages to reduce parameters and calculations without compromising precision. MobileNet is widely utilized in settings with limited computational resources, such as edge computing, IoT devices, and mobile phones. It has undergone iterative improvements with versions like MobileNetV1, V2, and V3, each introducing enhancements to the architecture, accuracy, and speed.

In the realm of real-time object detection for autonomous driving, SqueezeDet is a specialized model designed for identifying objects on roads. Introduced in a 2017 paper titled "SqueezeDet: Unified, Small, Low Power Fully Convolutional Neural Networks for Real-Time Object Detection for Autonomous Driving," SqueezeDet is built on the lightweight SqueezeNet architecture, well-suited for embedded and real-time applications. It processes whole images in a single pass using a fully convolutional neural network (FCN) architecture, generating bounding boxes and class predictions for recognized objects. SqueezeDet incorporates "squeeze and excitation" blocks to dynamically vary channel-wise scaling factors, improving object feature representation. The model predicts bounding boxes and assigns class labels to each box, achieving a balance between processing efficiency and accuracy for real-time object detection in autonomous vehicles.

MobileNet and SqueezeDet showcase the importance of efficient and lightweight neural network architectures in enabling deep learning applications on devices with limited computational capabilities.

MobileNet's versatility makes it a popular choice for various applications, while SqueezeDet excels in the specific context of real-time object detection for autonomous driving.

CONCLUSION

When integrated with analytics and metadata, object detection proves invaluable across diverse industries, especially in manufacturing and quality control. This powerful combination excels in identifying flaws on assembly lines, optimizing processes, and enabling preventive maintenance. For inventory tracking, metadata enhances supply chain efficiency, while in product monitoring, it predicts quality and facilitates customization. Integration is equally beneficial in tracking machinery functionality, enabling predictive maintenance, and ensuring compliance in sectors with stringent regulations. This amalgamation revolutionizes manufacturing and quality control, fostering data-driven decision-making, improving product quality, reducing waste, and enhancing overall productivity.

REFERENCES

- [1] Deci, "Deci Introduces YOLO-NAS - A Next-Generation, Object Detection Foundation Model Generated by Deci's Neural Architecture Search Technology," Deci, May 03, 2023. <https://deci.ai/blog/yolo-nas-foundation-model-object-detection>
- [2] S. S. A. Zaidi, M. S. Ansari, A. Aslam, N. Kanwal, M. Asghar, and B. Lee, "A survey of modern deep learning based object detection models," *Digital Signal Processing*, vol. 126, p. 103514, Jun. 2022, doi: <https://doi.org/10.1016/j.dsp.2022.103514>.
- [3] "SqueezeDet: Deep Learning for Object Detection," Mez Gebre. <https://mez.sh/2017/04/21/squeezedet-deep-learning-for-object-detection/> (accessed Dec. 22, 2023).
- [4] R. Alake, "How Does AI Detect Objects? (Technical)," Medium, Jan. 14, 2020. <https://towardsdatascience.com/how-does-ai-detect-objects-technical-d8d63fc12881>
- [5] D. S. Shenwai, "Top Object Detection Algorithms and Libraries in Artificial Intelligence (AI)," MarkTechPost, Jul. 18, 2023. <https://www.marktechpost.com/2023/07/18/top-object-detection-algorithms-and-libraries-in-artificial-intelligence-ai/> (accessed Dec. 22, 2023).
- [6] Rajath Karangara, "Unique Methods for Highly Populous Countries to Leverage Post-Pandemic Economy to Ramp Up Digital Payments," *SSRG international journal of computer science and engineering*, vol. 10, no. 7, pp. 21–26, Jul. 2023, doi: <https://doi.org/10.14445/23488387/ijcse-v10i7p103>.

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